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Supervised Classification of Satellite Images

Sayali Jog[1], Mrudul Dixit[2]
[1]Student, [2]Assistant Professor
Department of Electronics and Telecommunication, MKSSS's Cummins College of Engineering for Women, Pune, India.
[1]sayali8575@gmail.com, [2]dixitma@yahoo.com

Abstract: **Remote sensing is the method used to detect and measure target characteristics using electromagnetic energy in the form of heat, light and radio waves. Different applications where remote sensing is used are agriculture, disaster management, urban planning, water resource management, etc. The process of producing thematic map from remotely sensed imagery is called image classification. In one or more spectral bands digital numbers are used to represent spectral information. This information is used for digital image classification. Individual pixels are classified using this spectral information. For classification multispectral satellite images are used. Image classification can be supervised and unsupervised. The paper deals with the supervised classifiers namely minimum distance,support vector machine, maximum likelihood, and parallelepiped. The performance of these classifiers is judged on the basis of kappa coefficient and overall accuracy.**

Keywords: ***Classification, Confusion matrix, Kappa coefficient, Overall accuracy, Parallelepiped classifier, Remote sensing.***

I. INTRODUCTION

The science and art of obtaining and analysing information about phenomenon, area or object using device that is not in physical contact with area is called remote sensing. Platforms used in remote sensing are satellites and aircraft. These are used to determine amount of energy emitted by or reflected to the targets. Remote sensing providesconsistent andrepetitive view of the earth surface. In remote sensing, energy measurement takes place inreflected and emitted infrared, visible light, and microwave regions of electromagnetic spectrum. A discrete interval of electromagnetic spectrum is called spectral band. If information is collected over many spectral bands, it is referred as multispectral or hyperspectral data. Multispectral satellite images are used in remote sensing. Satellite images provide geographical information about large area and in relatively small time. Remotely sensed satellite images finds application in the areas of land degradation, geology, oceanography, soil classification, etc. [1], [2].

High spectral and spatial resolution images provide detail information about the target. In a fields of urban planning, land cover mapping, agriculture and habitat management, high spectral and spatial resolution satellite imagery is widely used. High spatial resolution images can be obtained using different sensors. The spatial detail in such imagery is limited by the number of pixel. In satellite image, all pixels can be grouped into one of the land cover class using classification process. Classification of satellite image is necessary to extract information depending on application [3].

Image classification generates thematic maps from remotely sensed images. Generated maps represent different objects on earth surface like vegetation, buildings and roads. Different satellite sensor produces different quality images. Accuracy of classification depends on satellite image quality.

Four steps are used for image classification, first is pre-processing of image followed by selection of particular criteria feature to describe the pattern then selection of classifier and lastly accuracy assessment of the image classification [2].

Image classification can be done using supervised classification and unsupervised classification.

Prior knowledge about study area is required for supervised classifier. In supervised classification image analyst select the training pixels. These pixels are used to obtained different land cover features. Using these features the classification is done.

Unsupervised classification does not require any prior knowledge of study area. In this classification large number of pixels that are unknown are examined which are further divided into different classes depending on natural groupings of images. For selection of training data image analyst is not required [4].

This paper contains following sections: Section II contains discussion on supervised classification algorithms. Section III includes statistical performance evaluation. Section IV compares different supervised classifiers and paper concludes in Section V.

II. SUPERVISED CLASSIFICATION TECHNIQUES

Different types of supervised classifiers are minimum distance, support vector machine, maximum likelihood, and parallelepiped.

A. *Maximum Likelihood Classifier:*

This algorithm involves supervised classification. Probability of pixels having particular class is the key element in maximum likelihood classifier [5]. These probabilities are equally likely for every class. It is parametric classifier that uses statistics of second order Gaussian Probability Distribution Function (PDF). It is optimal classifier if class PDF's are necessarily Gaussian and used as a reference for comparison of the different classifiers.

Gaussian PDF is given by,

$$f(X) = \frac{1}{\sigma\sqrt{2\pi}} e^{-(x-\mu)^2/2\sigma^2} \quad \ldots\ldots\ldots(1)$$

where, σ represents standard deviation and μ represents mean value.

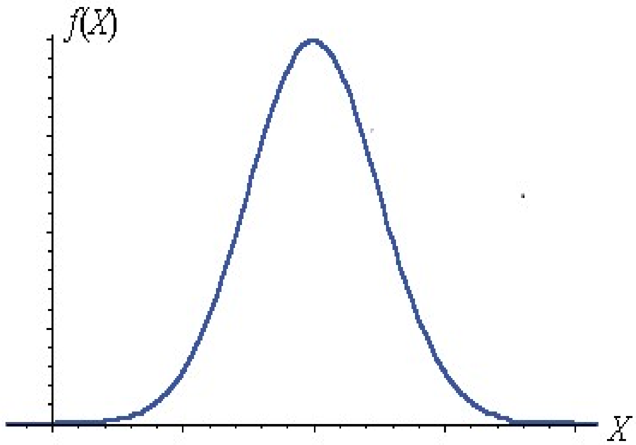

Fig. 1 Gaussian PDF

Maximum likelihood classifier produces accurate result. It requires more time due to computation complexity [2].

B. Minimum Distance Classifier:

It is depend on training data which is used to classify unknown image to the classes that minimizes distance between images and classes in multidimensional space. The index of similarity represents the distance. The minimum distance indicates maximum similarity. It is faster classifier as it requires less number of calculations. This is widely used classifier for image classification[6].

The following distances are used in minimum distance classifier process:

*1) Euclidian Distance:*It is used whenever population classes have different variances. Similarity index is theoretically similar to Euclidian distance.

$$d_k^2 = (X - \mu_k)^t . (X - \mu_k) \text{..........(2)}$$

Where, X is vector image data (n bands) and μ_k is mean of thekthclass.

*2) Normalized Euclidian Distance:*In case of different variance thesimilarity index is proportional to theNormalized Euclidian Distance.

$$d_k^2 = (X - \mu_k)^t . \sigma_k^{-1} . (X - \mu_k) \text{..........(3)}$$

σ_k is variance matrix

*3) Mahalanobis Distance:*The Mahalanobis Distance with variance-covariance matrix is employed when axes in feature space are correlated. Inverse covariance matrix is represented by$\sum_k^{-1}$.

Mahalanobis distance is given by,

$$d_k^2 = (X - \mu_k)^t . \sum\nolimits_k^{-1} . (X - \mu_k) \qquad \text{..........(4)}$$

C. Parallelepiped Classifier:

It is supervised, simple, fast and robust classifier [6]. It can be also called as multi-level slicing. It is based on division of every axis of multi-spectral feature vector. For each class the lowest and highest value on each axis is used to define decision boundary. From lowest and highest values of each class the accuracy is calculated [4]. If pixel is outside the box it remains unclassified. Pixel existing in overlapping boxes cannot be classified using parallelepiped classifier.

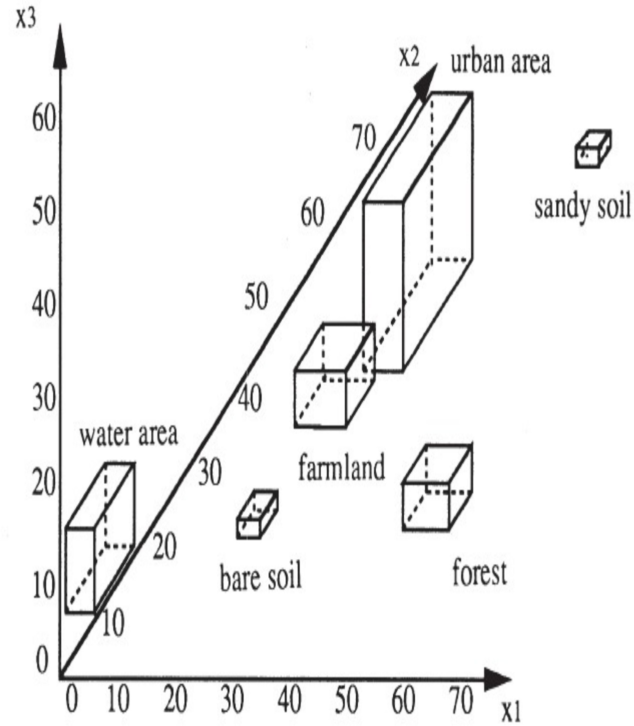

Fig. 2 Parallelepiped classifier in 3D feature space

D. Support Vector Machine (SVM):

In supervised classification system SVM is based on statistical learning. SVM is used for classification and regression. Different applications of SVM are face identification, text categorization, bioinformatics, database mining, handwritten character recognition and time series analysis [7], [8].

Testing and training is separated by SVM classifier. Several attributes and one target value is present in each instance in training set. Concept of decision surface is used in SVM. It is used to separate the classes in order to maximize the class margin. The decision surface is also known as optimal hyperplane. Support vectors are defined as data points close to decision surface. In training sample set creation key elements are support vectors [9].

Some variations of SVM are: 1) SVM can be modified by using nonlinear kernels to obtain a nonlinear classifier and 2) It can also be modified as multiclass classifiers by clubbing large number of SVM classifiers that are binary [10].

It minimizes number of misclassification. It is independent of feature dimensionality and produces accurate result. In SVM solution depends upon selection of kernel.

Different types of kernel used in SVM are linear, polynomial, radial basis function and sigmoid function.

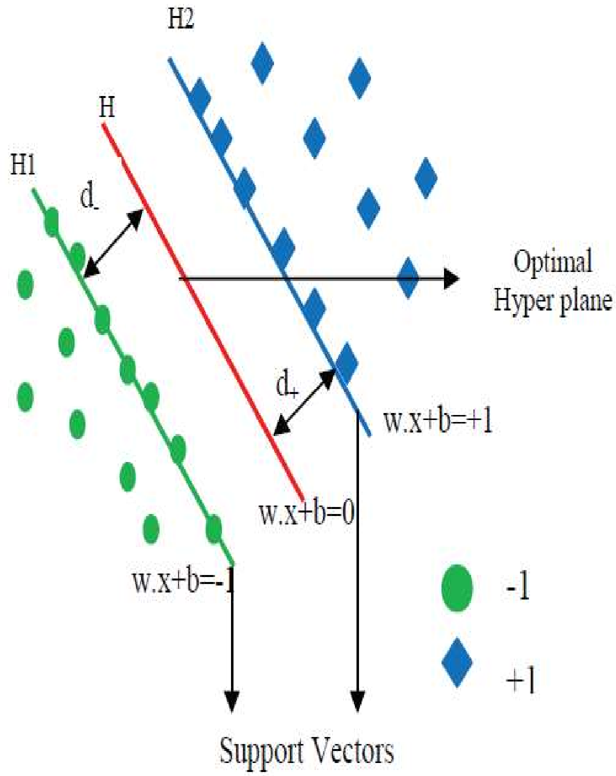

Fig. 3 Linear SVM methodology

III. STATISTICAL PERFORMANCE EVALUATION

A. Confusion matrix: [11]

Confusion matrix is also called as error matrix. It is a square matrix. Ona class by class basis it compares relation between classification result and reference data. Confusion matrix involves producer accuracy, user accuracy and overall accuracy.

*1) Producer accuracy:*Any classification scheme can be checked for accuracy using producer accuracy. It represents the percentage of a correctly classified ground class.

$$\text{Producer accuracy} = \frac{\text{Number of correctly classified pixels}}{\text{Total reference pixels}} \times 100 \quad \text{..........(5)}$$

*2) User Accuracy:*Performance of accuracy of classification result is represented by user accuracy.

$$\text{User accuracy} = \frac{\text{Number of correctly classified pixels}}{\text{Total classified pixels}} \times 100 \quad \text{..........(6)}$$

3) Overall Accuracy: Measure of overall behavior of the classifier is given by overall accuracy. It combines user and producer accuracy for complete image. Overall accuracy represents total percentage of correctly classified pixels.

$$\text{Overall accuracy} \frac{\text{Total number of correctly classified pixels}}{\text{Total reference or classified pixels}} \times 100 \quad \text{..........(7)}$$

B. Kappa statistics:

Kappa coefficient is measure of agreement or accuracy. It represents the degree of accuracy of image classification. Kappa statistic ranges between zero and one. The value greater than zero means classifiers performance is good. Higher the kappa statistic values better the classifier result.

IV. RESULTS

TABLE I. COMPARISON OF SUPERVISED CLASSIFICATION TECHNIQUES

Classification techniques	Key points	Advantages	Disadvantages
Maximum likelihood	Gaussian PDF	Accurate result	Slow due to computational complexity
Minimum distance	Euclidian, normalized Euclidian and mahalano-bis distance	Faster	Less accurate
Parallelepi-ped	Multi-level slicing	Simple, fast	Pixel outside box remains unclassified
SVM	Separates both linear and non-linear data, Kernel trick used for non-linear data, support vectors	Minimizes no of misclassi-fications, independent of feature dimensionality, accurate results	solution depend on selection of kernel, depend on size of data

TABLE II.SVM WITH DIFFERENT KERNEL TYPES

Method	Kernel type	Kappa coefficient	Overall accuracy (%)
SVM	Linear	0.8958	92.22
	Polynomial	0.9046	92.84
Maximum likelihood	-	0.85	88.30

Here performance of SVM classifier with linear and polynomial kernel is better than maximum likelihood classifier. Classification using SVM for linear and polynomial kernel is shown in figure 4 and 5 respectively.

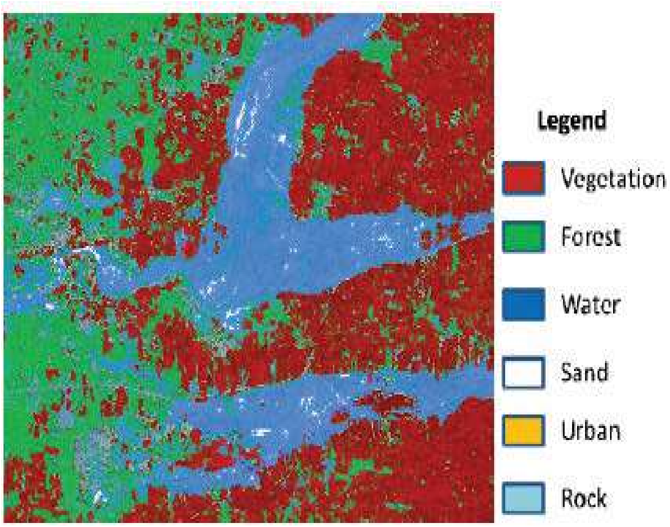

Fig. 4 Classification using linear kernel

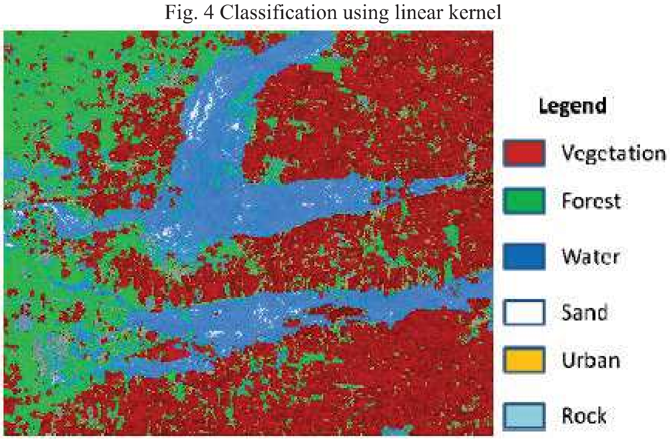

Fig. 5 Classification using polynomial kernel

From table it is clear that for Landsat 8, performance of maximum likelihood classifier is better than minimum distance classifier. For Landsat Multispectral Scanner (MSS), minimum distance classifier has high value of kappa coefficient and overall accuracy. For Landsat Thematic Mapper (TM) and Enhanced TM+ (ETM+) performance of maximum likelihood issuperior to minimum distance and parallelepiped classifier [12].

TABLE III.COMPARISON BETWEEN MAXIMUM LIKELIHOOD MINIMUM DISTANCE AND PARALLELEPIPED CLASSIFIER

Image	Type of classifier	Kappa coefficient	Overall accuracy (%)
Landsat 8	Maximum likelihood	0.8216	88.88
	Minimum distance	0.7893	78.88
Landsat MSS	Maximum likelihood	0.7532	> 79
	Minimum distance	0.7801	> 83
	Parallelepiped	0.7589	> 80
Landsat TM	Maximum likelihood	0.8960	> 93
	Minimum distance	0.8922	> 90
	Parallelepiped	0.8932	> 91
Landsat ETM+	Maximum likelihood	0.9052	> 96
	Minimum distance	0.8912	> 93
	Parallelepiped	0.8938	> 94
Landsat ETM+	Maximum likelihood	0.9052	93.75
Landsat 5 TM	Maximum likelihood	0.97	97.4

Kappa statistics and overall accuracy for Landsat 8 images is shown in figure below.

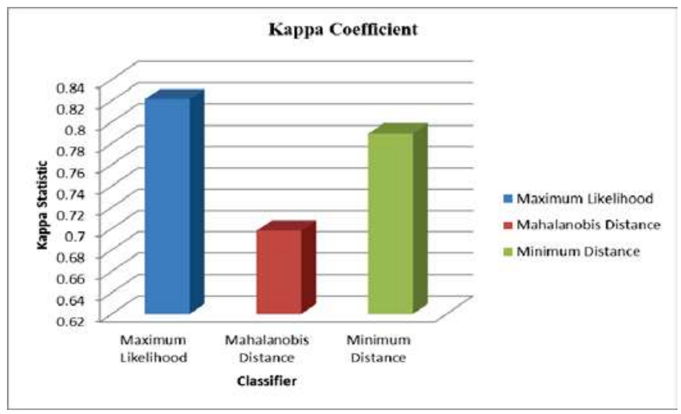

Fig. 6Comparison of Kappa Statistic for different type of classifier using Landsat 8 images

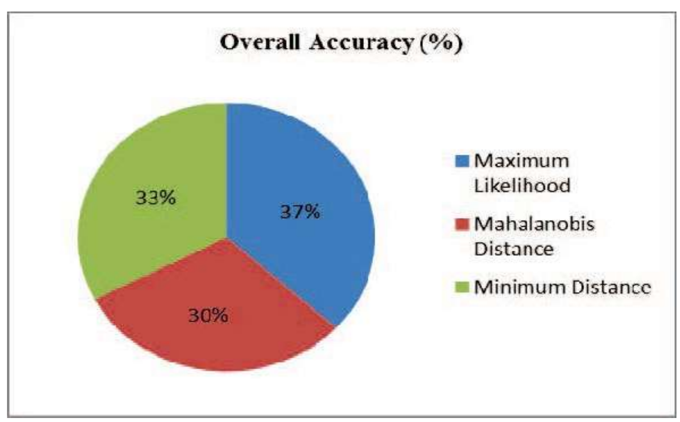

Fig. 7 Comparison of Kappa Statistic for different type of classifier using Landsat 8 images

Classification results for Landsat MSS, Landsat TM and Landsat ETM+ images using maximum likelihood, minimum distance and parallelepiped classifier are shown in the figure 8.

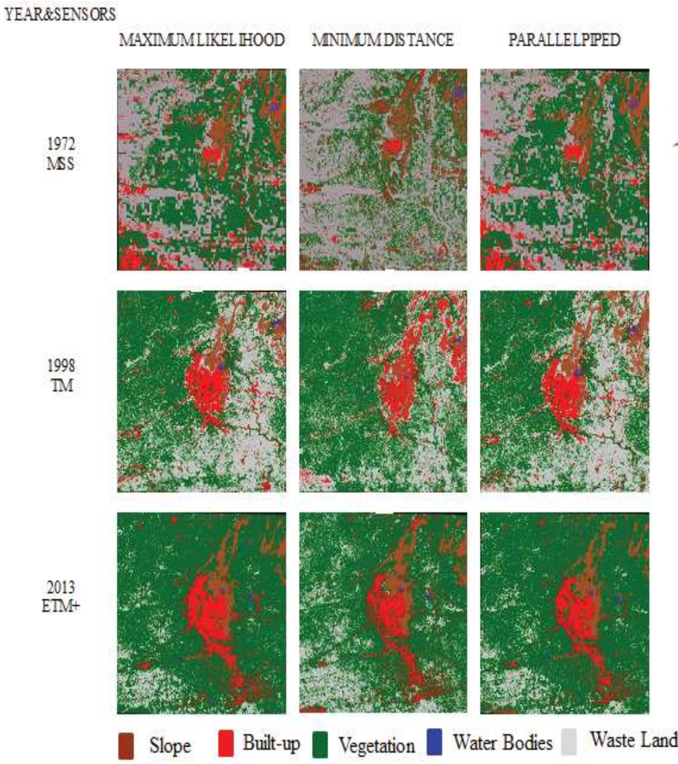

Fig. 8Remote sensing classification results

Classification result for Landsat ETM+ image using Maximum likelihood classifier and ERDAS Imagine 9.1 software is shown in figure 9.

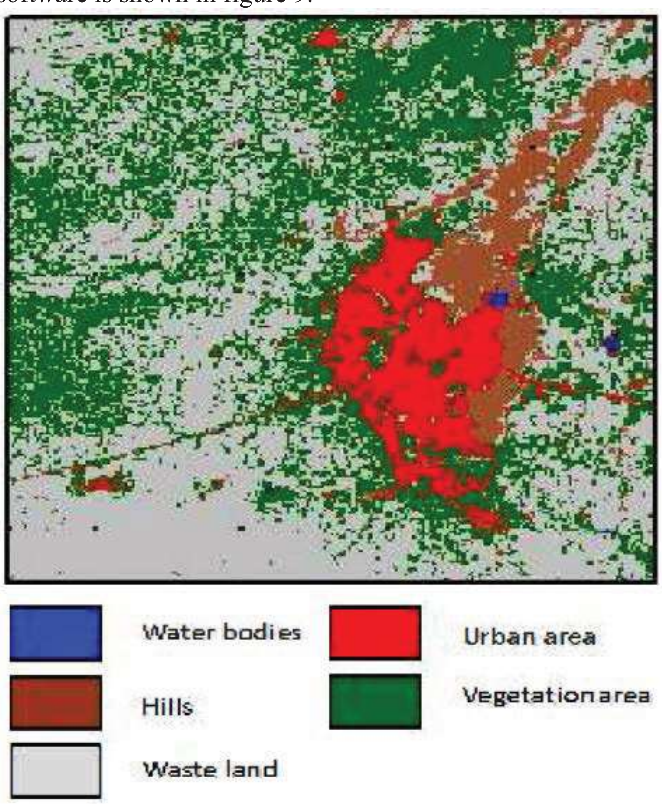

Fig. 9 Classification using maximum likelihood classifier

Classification using maximum likelihood classifier for Landsat TM image is given in figure 10.

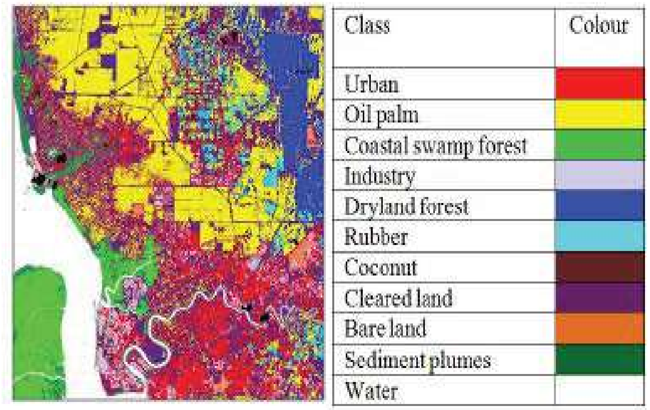

Fig. 10 Classification using maximum likelihood classifier

V. CONCLUSION

After analysing and comparing supervised classifiers namely minimum distance, support vector machine, maximum likelihood, and parallelepiped, it is indicated that for different types of images maximum likelihood classifier gives better results in terms of kappa coefficient and overall accuracy than minimum distance and parallelepiped classifier. Overall accuracy is greater than 88% and kappa statistics is greater than 0.82 for maximum likelihood classifier for all types of images except Landsat MSS images. Overall accuracy for SVM is more than 92% for both kernels.Sigmoid function and radial basis function can be used to improve accuracy of SVM. A

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